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State of Health Estimation using a Temporal Convolutional Network for an Efficient Use of Retired Electric Vehicle Batteries within Second-Life Applications

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Abstract

This paper presents an accurate state of health (SOH) estimation algorithm using a temporal convolutional neural network (TCN) for lithium-ion batteries (LIB). With its self-learning ability, this data-driven approach can model the highly non-linear behaviour of LIB due to changes of environment and working conditions all along the battery lifetime. The precise SOH predictions of the TCN are especially needed to ensure a safe and efficient usage of retired electric vehicle batteries within second-life applications. The provided network is trained and tested with data gathered from commercial industry applications in the domain of energy storage. It is shown, that even for dynamic load profiles, the TCN achieves a mean squared error (MSE) of less than 1.0%. Using this approach, the uncertainty of the heterogeneous performances and characteristics of retired electric vehicle batteries can be drastically reduced.

Keywords: lithium-ion battery, battery management system, state of health, second-life, artificial intelligence, temporal convolutional neural network, retired electric vehicle battery, stationary battery system.

1.2.1 Retired Electric Vehicle Batteries for Second-Life Applications

According to the Paris Agreement signed in 2016, over 190 countries agreed to reduce their greenhouse gas emissions by at least 40% until 2030 compared to 1990. To attain this objective, the usage of fossil fuels has to be drastically reduced, which is one reason why renewable energies are coming to the fore. For efficient and sustainable utilization of these intermittent energy sources, reliable and safe energy storage is an indispensable prerequisite. The lithium-ion battery (LIB) technology, with its high conversion efficiency, provides an efficient solution as dynamic energy storage. Thus, lithium-ion battery technology is a promising solution for sustainable transportation if the required energy comes from renewable energy resources. However, due to demanding operating conditions, an electric vehicle (EV) battery loses capacity and power over its lifetime. Typically, after 8 to 10 years of service, those batteries are retired due to capacity fade and power output that fails to meet range and performance requirements of modern EVs. In general, a retired battery of an EV can still provide 60-70% of its initial energy storage capability at the end of its vehicular life. In Figure 1.2.1, three prognoses of retired EV battery packs are shown.

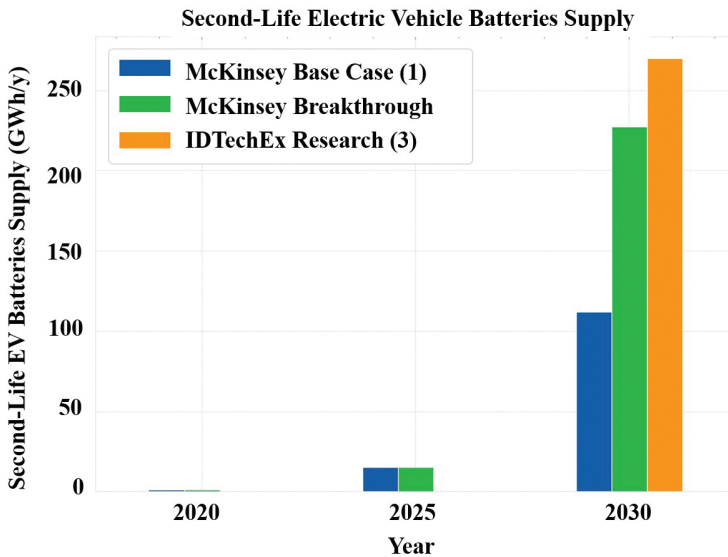


Figure 1.2.1 Retired electric vehicle (EV) battery packs prognosis in GWh per year [2][3].

According to IDTechEx research [2], by 2030 there will be over 6 million battery packs retiring from EVs per year. Since those batteries could contain 60-70 % of their initial energy storage capability, they can be further utilized in less-demanding applications such as stationary energy storage. However, there are still many challenges that have to be tackled in order to ensure a safe and economically valuable usage of retired EV batteries in second-life applications. In the following, four main challenges of second-life applications are described according to [1].

First, the competitiveness of second-life batteries with new generations of batteries is a big challenge. It is likely that when the worn-out EV batteries that are taken out of the car and could be used for second-life applications, there will be new generations of batteries with better quality and performance and at a lower price. Thus, the economical exploitation of second-life batteries will become even more challenging, while the CO₂ footprint of the battery manufacturing industry will have to be considered globally over the whole life-cycle. As a result, the cost competitiveness and the attractiveness of second-life batteries would be decreased, but the impact on the environment could become worse.

In addition, different regulations are a critical point. Second-life batteries are still not defined in the regulation in many countries. Since batteries are considered hazardous goods, the transportation requires special care and is, therefore, more expensive. Moreover, since the regulations of the electricity market in most countries are not fully open and transparent, the regulations of the battery storage for the energy market are not clear.

Another challenge is the design of the battery packs themselves. Battery packs are designed to optimally fulfill the requirements of the primary application they are used in, and that often requires technical and economical optimizations for the highest competitiveness on the market. Unfortunately, these optimizations are not optimal for repurposing the battery pack. Now, the vehicle manufacturers design and optimize the batteries only for being used in the vehicle, over 7-8 years. Battery repurposing cost is significantly affected by how the battery packs were initially designed. If components inside the battery pack are not compatible with stationary storage applications, additional costs for battery repurposing will result. For example, a car is designed for 300,000 km over 15 years and 10,000 h operation, while a stationary application is mostly requiring electronics supporting 24 h operation during 7 days in a week. A systemic design thinking that integrates the process of second-life repurposing into the initial battery pack design would simplify the repurposing procedure and reduce the repurposing costs

but would add with certitude costs on the implementation for the primary-life. Based on these considerations, it results that a regulatory way may be at least one enabler for second-life battery applications since the competitiveness in the primary application could be reduced significantly.

Finally, the spread and the uncertainty in the remaining battery lifetime and performance degradation in various energy storage applications is another main challenge. The lifetime and degradation of second-life batteries are quite heterogeneous and depending on a whole set of parameters (e.g., temperature, depth of discharge, current rates, mechanical vibrations), depending on how they were used in EVs and how they are going to be used during their second-life within stationary applications. Since each battery shows a different aging behavior depending on its chemistry (including the types and quantities of additives to the electrolyte), on its construction or its historical operating conditions within the vehicles, it is challenging to predict systematically the ageing behavior of the batteries during their second-life. A suitable evaluation and prediction of the second-life battery performance is essential for a safe and economically viable usage of retired EV batteries.

In the AI4DI project and with the demonstrator “autonomous reconfigurable battery system”, the challenge of uncertain second-life battery performance is tackled. Retired batteries (i.e., modules of packs) with very heterogeneous performances and characteristics are combined within a single battery system [18]. For this purpose, it is essential to determine the state parameters, like the state of health (SOH) of each battery accurately.

In this paper, it is shown how a temporal convolutional network (TCN) can be used for accurately predicting the state of health of a lithium-ion battery. In the following section, the fundamentals of SOH of lithium-ion batteries are recapitulated. Subsequently, the data measurement using the open-source battery management system foxBMS is covered. Afterward the TCN is introduced, and its building blocks are explained. In the subsequent chapter, the results of the SOH prediction using a TCN are presented and analyzed. Finally, the conclusion and outline of this work are given.

1.2.2 State of Health of Lithium-Ion Batteries

The performance of lithium-ion batteries is decreasing with time (i.e., calendric aging) and with utilization (i.e., cyclic aging). The two most characteristic parameters for measuring the current performance capabilities are the total battery capacity and the internal series resistance of the battery. The

capacity is decreasing, and the internal resistance is increasing due to unwanted side reactions and structural deterioration. As a result, an aged LIB can store less energy and deliver less power compared to a new LIB of the same type. The current aging status, also known as the state of health (SOH), is defined from 0 % to 100 %, where the SOH of a new LIB is defined to be 100 %.

This work focuses on the SOH derived from the energy capacity fade of a LIB as stated in Equation 1.2.1.

$$\text{SOH}_{Q_i} = \frac{Q_i}{Q_0} \quad (1.2.1)$$

where SOH_{Q_i} is the SOH after the i -th cycle, Q_i is the capacity after the i th cycle and Q_0 is the initial capacity at the lithium-ion battery's start of life. The capacities Q_0 and Q_i are determined using Coulomb Counting. The Coulomb Counting approach is a straightforward method that uses current integration. The capacity is computed by integrating the charge or discharge current over time. In order to realize the capacity computation and thus the SOH determination, the battery management system has to be introduced and how it is used for measuring battery usage data like the voltage, temperature, and current.

1.2.3 Data Measurement Using the Open-Source Battery Management System foxBMS

The battery management system (BMS) consists of the electronics and the embedded software to fulfil all tasks that ensure a safe, reliable and application specific optimal operation of the battery system. This includes measurement of all battery cell voltages in the battery pack, a use-case specific number of cell temperatures per battery module, and the battery pack current. Furthermore, additional measurement data can be used as input to ensure an optimal battery system operation, like e.g., pressure sensors or electrochemical impedance spectroscopy (EIS) measurements, with or without an additional sensor [8]. The BMS switches the electric power contactors of the battery system to ensure that the battery cells are not used outside of their safe operating limits. Pyro-fuses or electromagnetic fuses are used as last resort safety elements in the battery system to interrupt the battery current in case of a strong overcurrent or a short circuit. While the pyro-fuses are mostly actively controlled by the BMS, the electromagnetic fuses are triggered automatically by an overcurrent to ensure a shutdown if the battery is exposed to hazardous conditions.

In order to run a battery system in an application specific optimal operating window, battery models, ranging from cell to module and up to system models (e.g., equivalent circuit, physical- or heuristics-based ones) need to calculate battery state parameters, e.g., the previously mentioned SOH. The battery system must be able to perform the required model calculations and predict their output in real-time. Based on its own acquired measurement data, the implement application logic and the inputs from the higher-level control unit, the BMS can safely and optimal control the battery usage in the application.

To empower our partners and customers to build beyond state-of-the-art battery management systems, the Fraunhofer IISB has established a free, open and flexible Battery Management System R&D platform called foxBMS in 2016 [4, 5, 9]. In 2020, Fraunhofer IISB publicly announced that there is going to be the second generation of foxBMS [6] with enhanced safety and more data generation and connectivity possibilities, which then became available in 2021 [7]. foxBMS is a research and develop platform, which allows to rapidly development prototypes in the field of battery applications. These prototypes start from the simple implementation of drivers for innovative sensors, testing and benchmarking modern battery models on an embedded platform up to developing a full-customized battery system for a preproduction system, but also as starting point for advanced mobile and stationary battery powered products.

Whether battery usage data is generated in research projects, e.g., for an academic purpose for creating the most sophisticated and accurate models, or in a product, e.g., to increase the lifetime before end-of-life (EOL), it is mandatory to make the acquired measurement data available outside of the embedded system to learn from it, and feedback the gained knowledge. Figure 1.2.2 shows the information flow of the data pipeline.

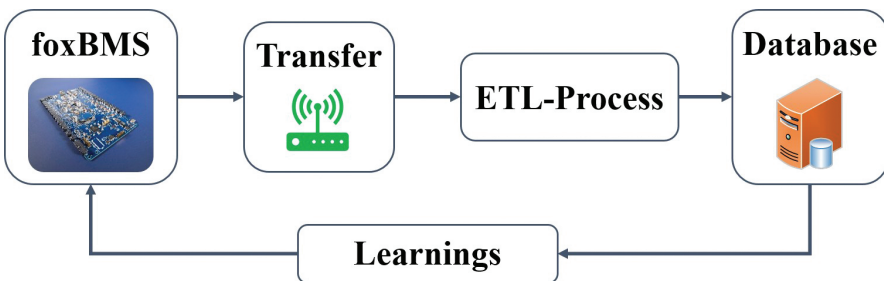


Figure 1.2.2 Measurement and data pipeline and the feedback loop into the BMS.

First, the measurement data is acquired by the BMS in the application. This raw data is then transferred and further processed in an ETL-process (*Extract, Transform, Load*) and stored in a database. This ETL-process is necessary, since the logged data stream in such a low-level system (e.g., CAN, Ethernet) cannot be directly used for modelling activities. Therefore, the output is converted and pre-processed in a data format that is reasonable for data analysis and model training.

After covering the fundamentals of the SOH and describing the data measurement using the open-source battery management system foxBMS, the data-driven approach for SOH prediction is introduced next.

1.2.4 Temporal Convolutional Neural Network for State of Health Prediction

Since the success of Deepmind’s WaveNet [12], a so-called deep neural network (DNN), similar but simplified networks have been successfully applied to more and more problems. This architecture family was first named temporal convolutional network (TCN) by Lea et al. [13]. A TCN can be differentiated by the following characteristics:

- 1) Causal convolutions are used to prevent the “leakage” of information from the future to the past.
- 2) The output sequence has the same length as the input sequence.

1.2.4.1 Causal Convolutions and Receptive Field

In contrast to 1D convolutions, the TCN uses *causal* convolutions. These are convolutions that only consider the $[t - k + 1, t]$ data at time t , where k is the kernel size. To ensure that the output sequence will have the same length as the input sequence, $(k - 1)$ data points have to be padded into the “past”.

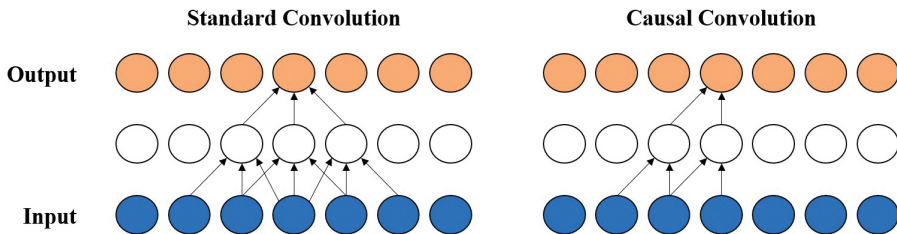


Figure 1.2.3 Comparison of a standard 1D convolution and a causal convolution.

The receptive field is the length of the input sequence of the TCN. When creating the model, the kernel size k and the receptive field R have to be specified. These two parameters then determine how many layers l are needed as it can be seen in Equation 1.2.2.

$$R = 2^l (k - 1) \tag{1.2.2}$$

1.2.4.2 Dilated Convolutions

The use of causal convolutions has the consequence that the network becomes deeper and deeper as the receptive field increases. As a result, not only the training duration but also the memory requirement increases. To counteract this problem, dilated convolutions are used. A dilation factor d indicates whether every data point is used ($d = 1$), only every second data point ($d = 2$), and so on. A too large dilation factor creates sparsity in the data, while a too small dilation factor does not solve the problems mentioned above. Therefore, the dilation factor is increased by a factor of two with each layer [12].

1.2.4.3 Residual Block

An additional method that ensures the stability and performance of deep networks is skip connections [14]. A skip connection does nothing more than adding the input to the output. In order to have a skip connection in a meaningful and useful way, a so-called residual block can be implemented. A residual block represents a layer of the network and ensures that local regeneration of a LIB can be captured [15] as it can be seen in Figure 1.2.5 at week 20.

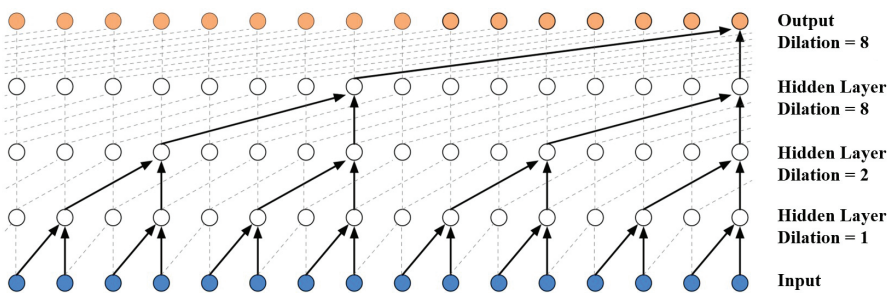


Figure 1.2.4 Dilated convolutions visualised [12].

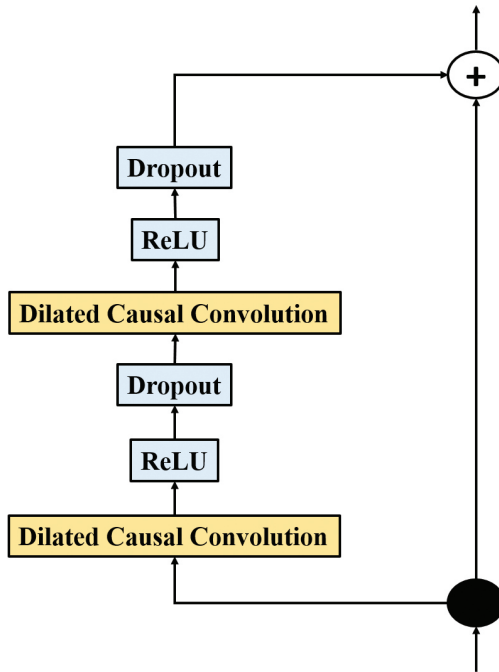


Figure 1.2.5 A residual block [12].

1.2.5 Results

In this chapter, it is shown how well the TCN performs the SOH prediction for a LIB. The TCN model was written in Python 3.8 and PyTorch 1.8. The training and experiments were run on a desktop PC with the following configuration: the CPU is AMD Ryzen 7 3700X, and the GPU NVIDIA GeForce RTX 3070. The TCN was trained on the public randomized battery usage data set from NASA Prognostics Center of Excellence [17]. This data set contains the data of 28 18650 lithium-cobalt-oxide cells with an initial capacity of 2.1 Ah. The battery cells are divided into seven groups of four cells each. Every group of cells was cycled with a different profile. A reference charge and discharge were carried out at regular intervals. Since the data set only contains time, current, voltage, and temperature the capacity and the resulting SOH were computed for each reference discharge. Then the calculated capacity and SOH were used to train the model. As input, the last 100 capacity values of a reference discharge were used and as output, the corresponding SOH was predicted. 22 cells were randomly picked as training

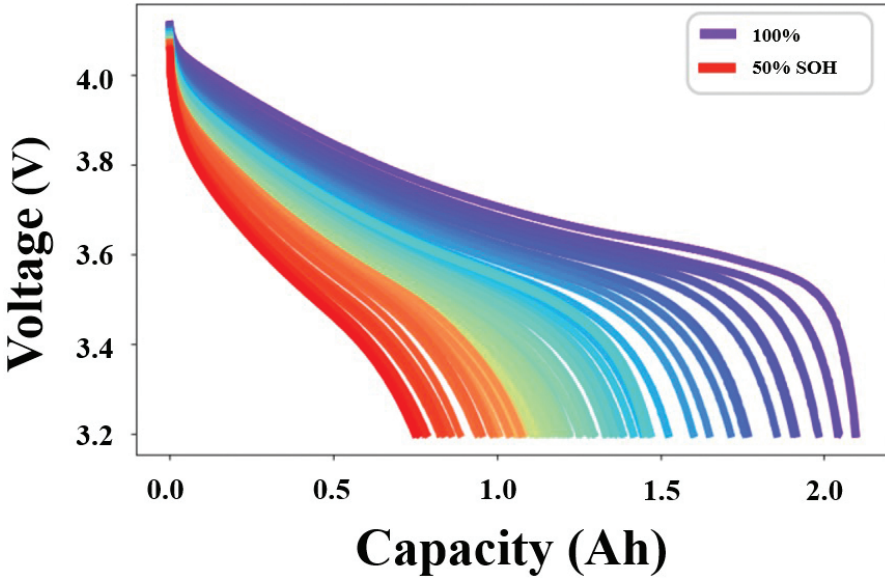


Figure 1.2.6 Constant current discharge profiles of a LIB [17].

data and the remaining six cells were used for testing purposes. The used model hyper parameters are a kernel size of 5, a dropout value of 0.2 and a batch size of 128. The model was trained for 2000 epochs.

In Figure 1.2.6, the reference discharge profiles are shown of a LIB is shown. The initial capacity of the LIB with 100 % SOH is 2.1 Ah. With increasing aging, the capacity and thus the SOH decreases. The neural network used in this work consists of three layers with seven neurons each. Furthermore, the TCN is trained by using Adam’s optimizer, which is an adaptive learning rate optimization algorithm that is specifically designed for deep learning applications [10]. The input for the TCN contains the capacity profile of the LIB.

In Figure 1.2.7, the SOH estimated by the TCN, and the reference measurement are plotted. The TCN predicts the SOH very accurately for the whole lifespan of the LIB. The integral mean squared error (MSE) for all predictions is approximately 0.9 %.

Here the high adaptability and self-learning ability from neural networks are coming to the fore, especially for real-world data with dynamically changing environment and operating conditions. Therefore, the TCN can provide reliable SOH estimations for the whole lifetime of LIB.

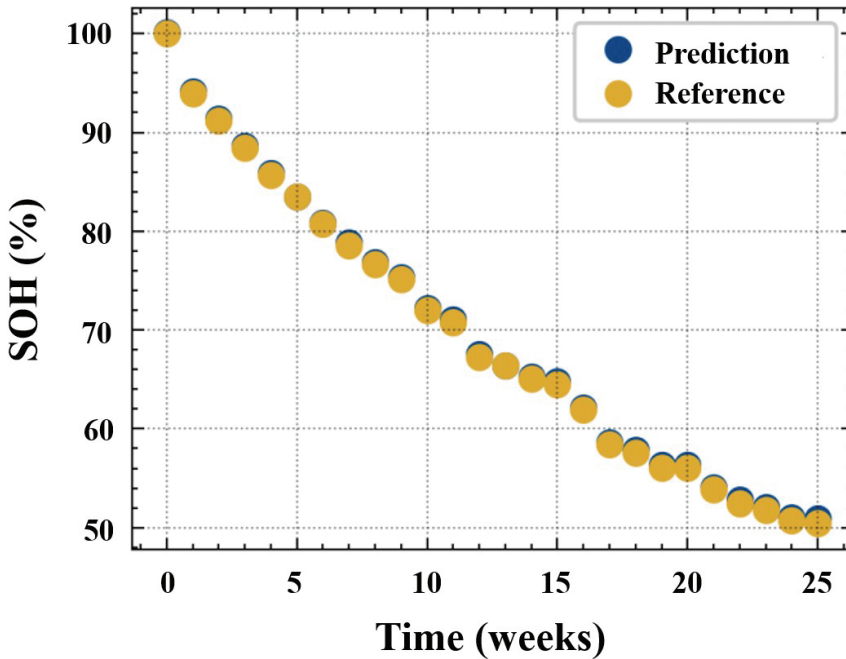


Figure 1.2.7 SOH prediction using a TCN with a reference measurement for the whole lifetime of a LIB.

1.2.6 Conclusion

For a safe, economically, and energetically efficient and sustainable utilization of retired EV batteries, reliable and accurate state parameter predictions are an indispensable prerequisite. To ensure a safe operation, an accurate prediction of the LIBs state of health (SOH) is essential. Traditionally, physical based SOH estimators are often limited due to their poor robustness regarding the highly non-linear dependence of the SOH on the changes of environment and working conditions during the operation. Data-driven approaches have shown their potential to overcome the drawbacks of traditional SOH estimation algorithms [16]. In the AI4DI project and its demonstrator “autonomous reconfigurable battery system”, a novel machine learning algorithm called TCN was implemented that combines beneficial properties of long-short term memory recurrent neural networks while being computationally more efficient [17]. In this paper, it has been shown that using a TCN the SOH of a LIB can be accurately predicted with an MSE error over the whole LIB lifetime with less than 1%. As a result,

with this approach, the uncertainty of the heterogeneous performances and characteristics of retired electric vehicle batteries can be drastically reduced.

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